Measuring climate resilience by linking shocks to development outcomes

Article (Accepted Version)

Measuring Climate Resilience by Linking Shocks to Development Outcomes

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ARTICLE HISTORY
Compiled October 31, 2019

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ABSTRACT
Adaptation finance addresses the effects of climate variability and change on development and physical insecurity. Yet, adaptation has proven difficult to systematically measure and assess, resulting in a lack of coherent and comparable evidence to learn about good adaptation practice. Measurement has become even more challenging since the integration of resilience into policy framings. Measuring climate resilience requires evidence of resistance to, and recovery from, shocks and stresses. But resilience of what, to what seldom guides the design of assessments. Researchers tend to use proxy indicators and aggregated units of analysis that cloud the relationships under study, and crucially, leave unclear the interactions between climate and development. This viewpoint documents these common barriers to progress in the field. It then outlines two methods for practitioners and researchers to link climate shocks and stresses to climate-sensitive development outcomes as a key first step to research and evaluation design. Both methods enable prediction of expected levels of development outcomes, given the extent of climate shocks and stresses, which is then comparable with actual levels achieved under climate resilience interventions. The product is standardized and comparable metrics to learn about the performance of climate adaptation policymaking and resilient development programming.

KEYWORDS
Resilience; Measurement; Shocks; Climate; Development.

1. Introduction

In Least Developed Countries (LDCs), intense rainfall, shifting seasons, dry spells, and drought negatively affect climate sensitive livelihoods (Niang et al., 2014). Climate change scenarios of 2.5oC temperature rise indicate reductions in Gross Domestic Product (GDP) across Africa and Asia (Plambeck, & Hope 1996; Tol, 2002), as hazards interact with social vulnerability to compromise production and immediate physical security (Bosello et al., 2012; Wisner et al, 2004). Negative feedbacks into other facets of development arise, influencing poor health outcomes and mortality rates from heat stress and malaria (WHO, 2012; McMichael et al., 2008).

Investments in climate adaptation increasingly focus on building resilience by preparing institutions and populations to resist and recover from climate shocks (Ayers and Forsyth, 2009; Barrett, 2017). But funding the climate resilience agenda is contingent upon showing programming to be effective and economically viable (DfID, 2011; IEG, 2013; Lamhauge et al, 2013; Pauw et al., 2016). Existing measurements of climate resilience (Jones, 2019) are based on poorly specified relationships between climate shocks and development outcomes. The field lacks a reliable body of research necessary to understand interactions between climate-development, learn from past performance, and systematically build knowledge through iterative replication of evaluation design (Douxchamps et al., 2017).

This viewpoint explains how efforts to measure climate resilience have failed to conceptually specify, or empirically test, which climate shocks are linked to the climate sensitive development outcomes under study. Crucially, this leaves researchers will little knowledge about the association between shocks and development outcomes as the basic starting point for larger multivariate research designs and modeling exercises. The current literature relies on aggregated units (e.g. households) and proxy indicators that: a) make verification of specific interactions between climate shocks and climate sensitive outcomes near impossible; and b) results in the central relationship of an evaluation resting on untested assumptions. As a consequence, studies offer no systematic basis on which to build knowledge.

This viewpoint proposes two practical methods of varying technical complexity to integrate climate shocks into assessments of climate sensitive development outcomes. The methods enable the inclusion of climate shocks into unidirectional relationships between shocks and outcomes, but omit the interconnected and indirect causality, and non-linearity, often the objective of systems analysis. The first method, suitable for practitioners and policy researchers, investigates which climate shocks are most associated with a climate sensitive development outcome. The approach does not assume that climate shocks (e.g. aggregate seasonal rainfall) are linked to development outcomes; instead it uses simple bivariate linear regression to test for a link between different weather-based indicators (e.g. number of dry days; rainfall over 7 days) and climate sensitive development outcomes. The magnitude and strength of the relationship determines which indicator(s) to include.

The second method is designed for researchers, and uses Gaussian Processes (GP) regression learning to simultaneously integrate all available climate-related indicators into a model to assess the impact on a climate sensitive outcome. The approach limits the inputs to climate only specifications and provides a multivariate and multi-dimensional model to link different types of climate factors to the given climate sensitive development outcome. This produces robust results in assessment settings with low numbers of entries, and better accounts for non-linear climate-development interactions.

The aim of both methods is to predict the 'expected' level of the climate sensitive development outcome *given the level of climate shock/stress experienced*. In the language of the evaluation community, the 'expected' level of the outcome represents the 'counterfactual'. This enables comparison of 'expected' levels of the climate sensitive development outcome with 'actual' values achieved under the climate resilience intervention. Results can be standardised to compare within and across projects/programmes to aid learning. An improved maize initiative [agronomic training and seed varieties (Lemu P3812W and Shone 30G19)], implemented in Hawassa, Ethiopia is used to illustrate.

The remainder of the viewpoint is ordered as follows: section 2 outlines the state-of-the-debate in measuring climate resilience, and identifies common barriers to progress in the field; section 3 demonstrates the two methodological options for assessing linkages between shock/stresses and development outcomes; section 4 outlines how to use the findings to measure climate resilience by comparing 'expected' levels of the development outcomes (i.e. counterfactual) with that observed after the resilience intervention; section 5 provides a brief summary.

2. Measuring Resilience: State of the Debate

Approaches to measure climate resilience vary considerably. These include assessments of 'capitals', or as is termed, capital asset approaches, derived from the livelihoods framework to scrutinizes components of resilient systems (ODI, 2016; Scoones, 2015); others monitor different areas of a systems ability to learn, demonstrate flexibility, and avail of options (Schipper and Langston, 2015), or the processes adopted through modes of operation (OECD, 2014); subjectivities and perceptions of communities about their own resilience (Choptiany et al., 2017; Clare et al., 2017); and more holistic assessments of system attributes (FAO, 2013).

This literature review is not an exhaustive account of efforts to measure climate resilience [see Douxchamps et al., (2017); ODI (2016); Barrett and Headly, 2014)]. Instead, it sets out a targeted sample of quantitative methodologies to identify common barriers to progress. The examples used tend to privilege rural settings, and are mainly concerned with agriculture- or livestock-based livelihoods.

2.1. *Indices*

Composite indices are commonly used methodologies (Prashar et al, 2012; Cutter et al., 2014; Smith et al., 2015). An early approach adapted to resilience was Alinovi et al.'s (2009; 2010; 2010a) index on food security for the Food and Agriculture Organisation (FAO) whereby households experience endogenous (e.g. disease) and/or exogenous shocks (e.g. climate) over time. Principal Component Analysis (PCA) is used in a latent variable framing of resilience dimensions (e.g. stability, social safety nets). PCA is again applied to reduce components into a single index measure. Recent refinements include the Resilience Index Measurement and Analysis (RIMA II) that facilitates household rankings more suitable for modeling determinants (FAO, 2016).

2.2. *Linear and Non-Linear Models*

In linear and non-linear models, resilience proxy indicators are used as either outcome variables or explanatory factors. Resilience, or resilience capacity, is modeled as: a) the probability of engaging in negative coping strategies after shocks (Bene et al., 2017); b) change in household hunger score and adequate food provision, based on self-reported overall shock exposure, self-reported flood shock exposure, and streamflow surplus data (Smith and Frankenberger, 2018); c) a perception-based ranking of recovery from shocks (Bower et al, 2016); d) recovery time to previous levels of consumption after climate shocks [deviations of Standardised Precipitation Evapotranspiration Index (SPEI)] (Vollenweider, 2015); e) change in household food security (Smith et al., 2015); f) recovery options for reducing differences in total/food consumption over time in shocked/not shocked households [defined as deviations of Standardised Precipitation Index (SPI)] (Asfaw et al., 2017); g) change in household Tropical Livestock Unit (TLU) when experiencing a drought (Ciss and Barrett, 2018); h) household welfare maintenance (i.e. consumption and child nutrition) after experiencing climate shock, using counterfactual estimation (Alfani et al., 2015); and i) changes in net agricultural and livestock income after experiencing cumulative high/low rainfall and extreme heat (Wineman et al., 2017).

2.3. *Economic Valuation*

Monetary assessment of climate resilience frames outcomes in terms of cost/benefit performance. Focusing on livestock, Venton et al (2010) models early response, late response, and a resilience scenario to establish the value of resilience interventions. Specifically, they compare delayed humanitarian drought response with early response using destocking methods; and combine with destocking and pre-emptive animal conditioning interventions. Comparing the resilience scenario with others represents the value of resilience.

More conventional cost-benefit analyses quantify the monetary benefits of adopting typhoon resilient housing (Tran Huu Tuan et al., 2015; Tran Huu Tuan, 2016), and compare with a counterfactual. The study uses key outcomes of working days lost from typhoons, evacuation costs, health expenses, building repairs, among others, to quantify past losses from typhoons. These metrics enable net-benefits estimates, which are compared across households using resilient housing measures and those without.

A forward-looking analysis estimates net-benefits subject to variable probability of typhoon occurrence rates under climate change.

Table 1 here.

2.4. *Barriers to Measuring Resilience*

Over-aggregated units of analysis, and untested assumptions about linkages between shocks and development outcomes, represent the main barriers to assessing resistance and recovery to/from climate shocks. A lack of conceptual and empirical specification about how assumed shocks interact with development outcomes confounds the very foundation of efforts to design research/evaluations. When shocks are included, they qualify as such based on: a) assumptions those chosen are primary; and b) arbitrary thresholds with little or no investigation of how context influences normal climate variability to become hazardous. Inadequate shock metrics are then modeled to interact with aggregated units that have uncertain climate sensitivity. Finally, a focus on recovery of 'shocked' units misses resistance as the first and most preferable attribute of a resilient system.

2.4.1. Aggregated Units

Researchers tend to assess resilience of aggregated systems or units, particularly households and communities (Alfani et al., 2015; Vollenweider, 2015; Barrett and Cisse, 2018), and even sectors and national economies (Hallegatte, 2014). Development outcomes are most often assumed to concentrate within household units as the site of risk management decision-making (FAO, 2017), but also the default scale to assess performance of development programming (Khandker et al., 2009).

But climate shocks take many forms and interact in specific ways with development. Shocks do not universally impact the household as a unit, neither do they affect households in similar ways, but instead may affect one or a series of individuals or observable components within each household (Paavola, 2008). For example, heavy rainfall may cause flooding that physically breaches a dwelling, but have negligible direct impact on economic and social status of the family therein (e.g. consumption). The assessment of resistance and recovery is confounded from the outset without first conceptualizing and then measuring the magnitude and strength of the link between climate shocks and climate sensitive development outcomes.

The use of aggregated units recalls the classic question: resilience of what, to what? (Carpenter et al., 2001; Chuan and Fei, 2016). Measuring resilience requires both a specification of the system, and testing for hazard(s) potentially disturbing subcomponents (Skylas et al., 2002; and Larsen et al, 2008). This specification should serve as the basis of research designed to trace and isolate affects of interventions.

2.4.2. Proxy and Aggregated Metrics

Indices describe relative levels of components thought to improve resilience, rather than detailed insight into the performance of newly introduced technologies (Levine, 2014). They are not designed to observe mechanisms generated by engaging with resilience projects or programmes (Asadzadeh et al., 2017), which it itself clouded when using aggregated units (FAO, 2017). Such findings offer little prescription to improve projects or programming.

Many focus on modeling metrics of household consumption (Asfaw et al., 2017;

Alfani et al., 2015), but omit the initial investigation into how the specific shock(s) have an effect on household consumption. Testing for the precise form of climate variability that is hazardous to consumption is analytically impossible, because consumption has no direct climate sensitivity. Consumption is a consequence of many factors some with climate sensitivity (e.g. rain-fed agriculture), and some without climate sensitivity (e.g. non-farm wage labour, remittances) (Tschirley and Weber, 1994).

2.4.3. Resistance and 'Experiencing' Shocks

Resistance is often omitted from resilience assessments (Bene et al., 2017; Bower et al, 2016). Highly resistant systems avoid climate shocks, remain in equilibrium, and circumnavigate the need to recover (Folke, 2006). Physical climate variability (e.g. storms) only become hazardous when social systems are sensitive to change (e.g. informal housing). Climate hazards are essentially social constructs that are experienced when social systems cannot withstand change. Therefore, resilience programming can be improved by the identification of well-specified coping thresholds (Levine, 2014) within climate-development interactions.

Focusing on recovery from climate shocks alone only measures 'bounce back' as a second, less preferable, stage of resilience, after resistance thresholds are breached [anticipate in the A2R framing (UN, 2017)]. It is necessary to integrate physical climate data with social and economic indicators to identify those dealing with variability and avoiding hazards (Brooks et al., 2014). Contextual knowledge enables relevance of climate data to identify where shocks are likely to impact productive systems and physical circumstances. Only once climate shocks to development are identified, and the appropriate linkages made, can robust assessments follow.

3. Methodologies to Link Climate Shocks with Climate Sensitive Development Outcomes

This section outlines two methodologies to link climate shocks to a development outcome. The methods use past relationships between climate variability and a development outcome to predict the future focusing on trends over time, which omit aspects of non-linearity and surprise characteristic of resilience. An improved maize intervention [i.e. Maize Yield Per Hectare (MYPH) as development outcome see end note 1] within a rural initiative to improve the climate resilience of smallholder farmers around Lake Hawassa, Ethiopia, is assessed using two statistical techniques bivariate linear regression and GP regression learning. Farmers received agronomic training on soil management, planting techniques, and a choice between two maize seed varieties (Lemu P3812W and Shone 30G19) understood to perform under disease and drought stress. The exposure cycle is short, with resistance and recovery to/from climate shocks confined to a growing season. The aim is to determine the 'expected' level of MYPH i.e. our counterfactual given a level of climate shock/stress.

3.1. *Climate Shocks and Stresses to MYPH Using Linear Regression for Prediction*

Figure 1 shows the bivariate links between climatological data and MYPH in two Woredas (i.e. district administrations) over a six-year period. Indicators selected are known potential shocks: aggregate rainfall is a commonly identified hazard to MYPH performance (Tadross et al, 2009); other hazards include prolonged dry spells (consecutive dry days), and intensive periods of rainfall [total rainfall (mm) over 7-day period] (Barron et al., 2003). Extreme temperatures are also hazardous to MYPH (Muchow et al, 1990; Bassau et al., 2014), and maximum and minimum temperatures from the season are included.

Figure 1 here

Figure 2 here

Simple bivariate regression establishes which climate variables best relate to the development outcome of MYPH. The decision-making criteria are: a) the strength of the relationship (the slope); b) the direction (positive/negative); and c) the observable pattern of data (if low numbers undermine claims of statistical significance). Aggregate rainfall and minimum temperature have some relationships to MYPH performance (e.g. lower rainfall and temperature place downward pressure on yield), which corresponds with agronomic literature (Hoffman et al., 2017).

Despite linear relationships being the focus, the complexity and interdependence of these factors is worthy of discussion. First, there is likely a threshold beyond which increases in dry days changes from having a positive to a negative effect on production (i.e. suggesting non-linearity). Second, it is also likely a similar threshold with aggregate rainfall above 400mm, the emerging relationship weakens (albeit based on low entries). In wetter years the positive affect of rainfall may be offset by crop damage, or pests/diseases.

Using aggregate rainfall and minimum temperature to MYPH, Figure 2 shows how the straightforward regression line can be used to predict MYPH given a level of climate shock. By inserting climate-related values for 2015/6 into the equation [aggregate rainfall = 449mm (2015) and 179mm (2016); minimum temperature = 11.6oC (2015) and 12oC (2016)], the model estimates expected MYPH. For 449mm (2015) and 179mm (2016) of rainfall, the yield estimate is 6231 kg and 5882 kg respectively (top graph); for minimum temperatures of 11.6oC and 12oC, the estimate is 6529 kg and 6387 kg respectively (bottom graph). Expected yields i.e. our counterfactual are now ready to compare with actual yields for those receiving improved seed.

3.2. *Climate Shocks and Stresses to MYPH Using Gaussian Processes Regression Learning for Prediction*

Another methodological option is to predict the value of expected MYPH using all climate variables in a multivariate model. The application of GP regression learning can produce robust predictions with low numbers of entries, while better accounting for non-linear interactions in the data. The approach also accounts for the likelihood that more than one climate shock/stress is adversely affecting the climate sensitive outcome at the same time. Importantly, the GP approach produces a well-calibrated uncertainty estimate (an error bar) for its predictions, and this error bar can be useful for building confidence about the proposed climate resilience measure.

In a GP regression learning setting, we are given a data set of N input-output pairs $\{(x_1, y_1), \ldots, (x_N, y_N)\}$ with input $x_n \in \mathcal{X}$ and output $y_n \in \mathbb{R}$ and the goal of learning is to infer a latent function $f : \mathcal{X} \rightarrow \mathbb{R}$. For the purpose of measuring climate resilience, x_n are climate related variables, and y_n refers to the MYPH that year. In the GP regression framework, at input x_n, instead of directly observing the latent function value $f(x_n)$, what we observe is a noisy version of it. The relationship between the output and the latent function value is given by $y_n = f(x_n) + \epsilon_n$. The ϵ_n is a noise term and it is assumed to be independent and normally distributed with zero mean and variance σ^2, that is $\epsilon_n \sim \mathcal{N}(\epsilon_n|0, \sigma^2)$. In order to make an inference about the input-output relationship, we proceed by imposing a zero-mean Gaussian process prior on the latent functions f. If we let $\mathbf{f} = (f(x_1), \ldots, f(x_N))^\top$ be an N-dimensional vector of function values at N input locations x_n, the prior distribution can be written as

$$P(\mathbf{f}|X = (x_1, \ldots, x_N)^\top) = \mathcal{N}(\mathbf{f}|0, K),$$

where $K \in \mathbb{R}^{N \times N}$ and $K_{ij} = k_\theta(x_i, x_j)$. The likelihood of the function given the observed data can be written as

$$\begin{aligned} &P(\mathbf{y} = (y_1, \ldots, y_N)^\top|\mathbf{f}, X) \\ &= \prod_{n=1}^{N} P(y_n|x_n, f) = \mathcal{N}(\mathbf{y}|\mathbf{f}, \sigma^2 I), \end{aligned}$$

where I is the identity matrix. The above definition of the likelihood function follows directly from the independence assumption about the noise process. By integrating out the latent function variables $\mathbf{f}$ (that is by averaging over all possible function values), we end up with the so-called marginal likelihood term:

$$\begin{aligned} P(\mathbf{y}|X) &= \int d\mathbf{f} P(\mathbf{y}|\mathbf{f}, X) P(\mathbf{f}|X) \\ &= \mathcal{N}(\mathbf{y}|0, K + \sigma^2 I) \end{aligned}$$

The above quantity measures the average fit of a model class to the given data set. This is to be constrasted with a maximum likelihood fit, $P(\mathbf{y}|\mathbf{f}_{\mathrm{ML}}, X)$, that finds a single best function fit from a specific model class according to a maximum likelihood criterion $\mathbf{f}_{\mathrm{ML}} = \arg\max_{f \in \mathcal{F}} P(\mathbf{y}|\mathbf{f}, X)$. Here $\mathcal{F}$ denotes the model class, for example a linear function class. The $P(\mathbf{y}|X)$ averages over all functions in the model class where the choice of the model class is determined by the covariance function.

Finally, by invoking the Bayes' rule, $P(\mathbf{f}|\mathbf{y}, X) = P(\mathbf{y}|\mathbf{f}, X)P(\mathbf{f}|X)/P(\mathbf{y}|X)$, we will have a Gaussian posterior distribution as follows

$$\begin{aligned} &P(\mathbf{f}|\mathbf{y}, X) = (\mathbf{f}|\mu_{\mathbf{f}}, \Sigma_{\mathbf{f}}) \\ &\quad \text{where,} \\ &\qquad \mu_{\mathbf{f}} = K(K + \sigma^2 I)^{-1}\mathbf{y} \\ &\qquad \Sigma_{\mathbf{f}} = K - K(K + \sigma^2 I)^{-1}K. \end{aligned}$$

From the posterior distribution, we can compute the predictive distribution on the new output y^* at a input location x^*, as follows:

$$P(y^*|\mathbf{y}) = \int df^* P(y^*|f^*, x^*) \int d\mathbf{f} P(f^*|\mathbf{f}) P(\mathbf{f}|\mathbf{y}, X).$$

The $P(f^*|\mathbf{f})$ is a conditional multivariate Gaussian due to the GP marginalisation property (Rasmussen and Williams, 2006). Since all the terms are Gaussians, the above

$P(y^*|\mathbf{y})$ is again a Gaussian distribution with a mean $\mu_{y^*} = k^*(K + \sigma^2 I)^{-1}\mathbf{y}$ and a variance $\sigma^2_{y^*} = k(x^*, x^*) + \sigma^2 - k^{\top,*}(K + \sigma^2 I)^{-1} k^*$ with $k^* \in \mathbb{R}^{N\times 1}$ and $k^*_n = k_\theta(x^*, x_n)$.

To make a point prediction, we follow the Bayesian decision theory and minimise the expected loss $\Delta(\cdot,\cdot)$ with respect to the predictive distribution $\arg\min_{y_{\text{point}}\in\mathbb{R}} \int dy^* \Delta(y_{\text{point}}, y^*) P(y^*|\mathbf{y})$. For a squared loss function, $\Delta(y_{\text{point}}, y^*) = (y_{\text{point}} - y^*)^2$, the optimal point prediction is the mean of the predictive distribution μ_{y^*}.

Figure 3 shows two of the eight dimensions of the input-output relationship. The blue circles are the true values in the dataset. The red line is the prediction line from the GP Regression Learning, and the grey band is the 95% confidence interval. Each of the two dimensions show a prediction specific to that dimension. When all dimensions are included in the final model, the prediction for expected MYPH is 6734 kg per hectare for 2015 and 6191 kg per hectare for 2016.

Figure 3 here

4. Comparing Expected and Actual MYPH

Figures 4 and 5 enable comparison of 'expected' MYPH based on the bivariate regression model i.e. aggregate rainfall and minimum temperature with actual MYPH from seed and training intervention. Actual yields were 6385 kg (2015) and 3048 kg (2016); the difference between 'expected' and 'actual' yields for both hazards is as follows: for aggregate rainfall estimates, an additional 154 kg (+2.4%) in 2015 is offset by a significant underperformance of 2834 kg (-48.2%) in 2016. For minimum temperature, 'expected' versus 'actual' yields indicate a loss of 144 kg (-2.2%) in 2015 was followed by a more significant loss of 3339 kg (-52.3%) in 2016.

Figure 4 here

Figure 5 here

Figure 6 compares 'expected' MYPH based on the prediction of the GP regression learning multivariate model i.e. all potentially associated climate variables with actual MYPH from the improved seed varieties. The findings are similar to those developed using the bivariate linear regression model. Again, actual MYPH was 6385 kg (2015) and 3048 kg (2016); the difference between 'expected' and 'actual' yields was -349kg (-5.4%) in 2015 and -3143 kg (-50.7%) in 2016.

Figure 6 here

The overall findings on Figures 4-6 show only a faint signal that the improved seed variety is able to resist and recover from the moderate climate shock of 2015, but significantly under-performed when exposed to the El Niño of 2015-2016. The improved maize variety demonstrated poor tolerance to the severe climate shock most likely attributable to the significant reduction in aggregate rainfall and increased consecutive dry days. The markedly large gap in expected and actual maize yield may indicate either: a) the seed variety was unsuitable for the full range of likely rainfall events in the context; or b) a result of insufficient variation in historical data to make a robust prediction of expected yield under such extreme conditions.

Finally, converting variation between 'expected' and 'actual' MYPH into z-scores can facilitate comparisons of different climate resilient intervention types. If other assessments followed the same process, standardization in deviations between 'expected' and 'actual' results would enable comparisons of different climate sensitive development outcomes, exposed to different types of shock, and with different measures designed to improve climate resilience under investigation. This provides policymakers with reliable metrics to draw conclusions about the performance of interventions to facilitate resistance and recovery from climate shocks and stresses. For instance, the same process can be conducted for rates of malaria infection intensity and significant rainfall events, albeit only in the context of reductionist unidirectional relationships between the interventions and key outcomes. The standardised differences between model predictions of 'expected' malaria rates and the 'actual' rates are comparable with those of, say, the standardised differences between the 'expected' and 'actual' MYPH demonstrated above.

5. Summary

This viewpoint illustrated the challenges researchers currently encounter when measuring resilience, and proposes two methods to test the assumptions about linkages between climate shocks to development outcomes.

By integrating climatological data directly with climate sensitive development outcomes, researchers and practitioners can determine intervention performance in terms of resistance and recovery to/from climate shocks in evaluation settings where such relationships are observable. Maize production cycle is short between 4-6 months and the methodology allowed an examination of climate impacts over successive exposure cycles. Other outcomes may take longer to assess, such as resilience of homesteads to inundation and climate shocks on other aspects of human wellbeing as measured by sub-sets of conventional development indicators (e.g. components of health or poverty).

Researchers and practitioners often need to account for longer time dynamics around resistance and recovery, but can use the same process for linking climate shocks to outcomes. For instance, regarding household inundation, metrics such as the expected and actual speed of return after relocation would need to be combined with assessments of absolute or partial resistance to flooding events. Either way, the broad consensus will likely remain that resilience is a practical framing concept, but challenging to assess and evaluate.

Notes:

1. Agronomic training and enhanced drought- and disease-resistant seed provision was integrated within subsistence smallholder farming systems. Maize yield per hectare is a direct indicator of a smallholder farmers ability to raise productivity, meet basic nutrition needs, accumulate asset and make development progress under climate stress.

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